Leveraging Hashtag Networks for Multimodal Popularity Prediction of Instagram Posts

Yu-Yun Liao

Graduate Institute of Linguistics, National Taiwan University

Introduction

With the increasing commercial and social importance of Instagram in recent years, more researchers begin to take multimodal approaches to predict popular content on Instagram. However, existing popularity prediction approaches often reduce hashtags to simple features such as hashtag length or number of hashtags in a post, ignoring the structural and textual information that entangles between hashtags. In this paper, we propose a multimodal framework using post captions, image, hashtag network, and topic model to predict popular influencer posts in Taiwan. Specifically, the hashtag network is constructed as a homogenous graph using the co-occurrence relationship between hashtags, and we extract its structural information with GraphSAGE and semantic information with BERTopic. Finally, the prediction process is defined as a binary classification task (popular/unpopular) using neural networks. Our results show that the proposed framework incorporating hashtag network outperforms all baselines and unimodal models, while information captured from the hashtag network and topic model appears to be complementary.

Methodology

Model Structure

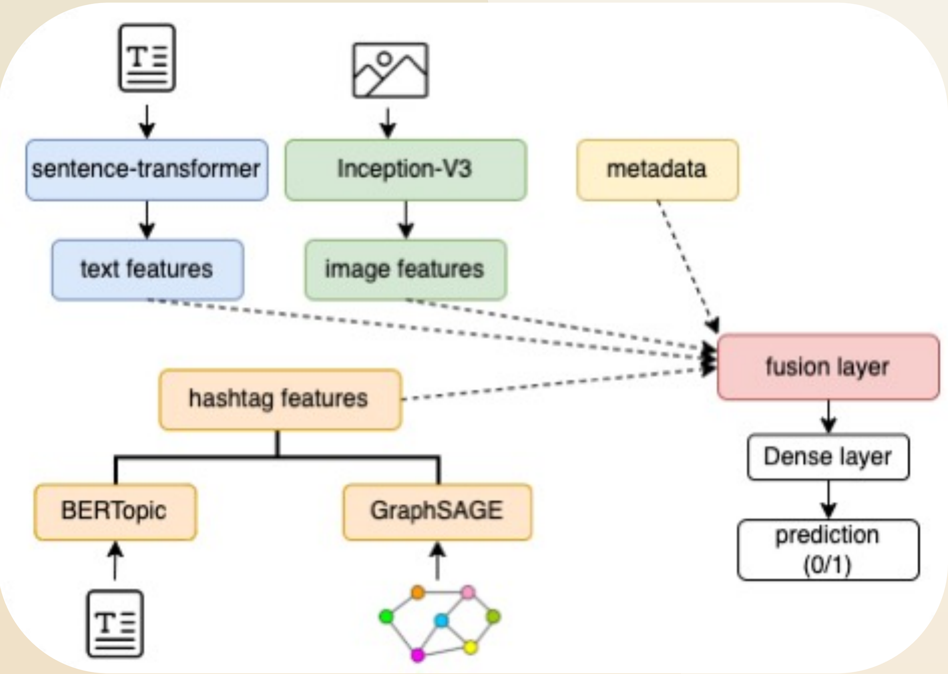

Figure 1. Illustration of the multimodal framework leveraging hashtag network

Feature	Description
timeofpost	Time of post in a day
text_length	Length of post caption
hashtag_num	Hashtag count in a post

Table 1. Additional Metadata

Figure 1 illustrates the multimodal post representation framework used in this study. For text modality, each post caption is encoded using sentence-transformers. For image modality, each image is represented using the Inception-V3 featurizer from pic2vec. As for hashtag modality, two kinds of embeddings are involved: topic embeddings calculated from BERTopic and average node embeddings calculated from the hashtag network using GraphSAGE. Last but not least, 3 additional metadata are used in the framework, as shown in table 1. The four components – text, image, hashtags modalities and metadata, are then concatenated in the fusion layer. Ultimately, the concatenated features are connected to a dense layer outputting the final prediction as either a popular post (1) or unpopular post (0).

Defining Popular Posts

The method used in this study mostly follows that of Carta et al. (2020); however, instead of calculating the likes moving average (LMA) as the popularity metric, the present study calculates the engagement moving average (EMA). Engagement *E* in this study is defined as the number of likes count plus 2 times the number of comments in each post. Let Pi be the ith post in an influencer account, the formula can be shown as follows:

$$E(P_i) = likes\_count(P_i) + 2*comments\_count(P_i)$$

Similar to Carta et al. (2020)'s calculation of LMA, the EMA (engagement moving avearge) of a given post Pi is calculated by averaging the engagement of its previous k posts, as shown in the following formula:

$$EMA_k(P_i) = \frac{\sum_{i-k}^{i-1} E(P_i)}{k}, i > k$$

Finally, the popularity class (PC) of a given post Pi can be derived by comparing its engagement with its EMA times a parameter Δ , as shown in the following conditional formula:

$$PC_{k,\Delta}(P_i) = \begin{cases} 1\,(popular), & if\ \ E(P_i) > EMA\_k(P_i) * (1+\Delta) \\ 0(unpopular), & otherwise \end{cases}$$

The parameter Δ controls the strictness of the threshold; for example, when Δ = 0.1, the engagement of a post needs to be greater than 1.1 times its EMA in order to be labeled as a popular post. In other words, as Δ becomes higher, it will also be harder for a post to become a popular post, decreasing the total number of popular posts as well.

LOPE Lab

My Github

Contact information: yuyunliao0821@gmail.com

Results

Model performance

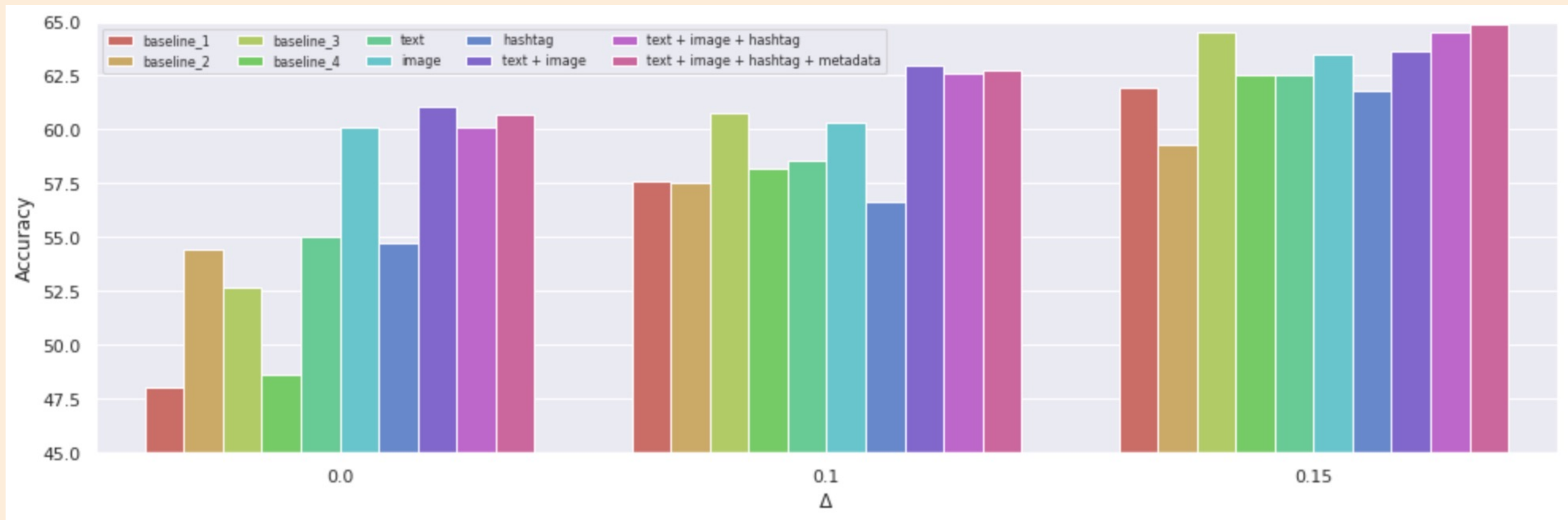

Figure 2. Model accuracy

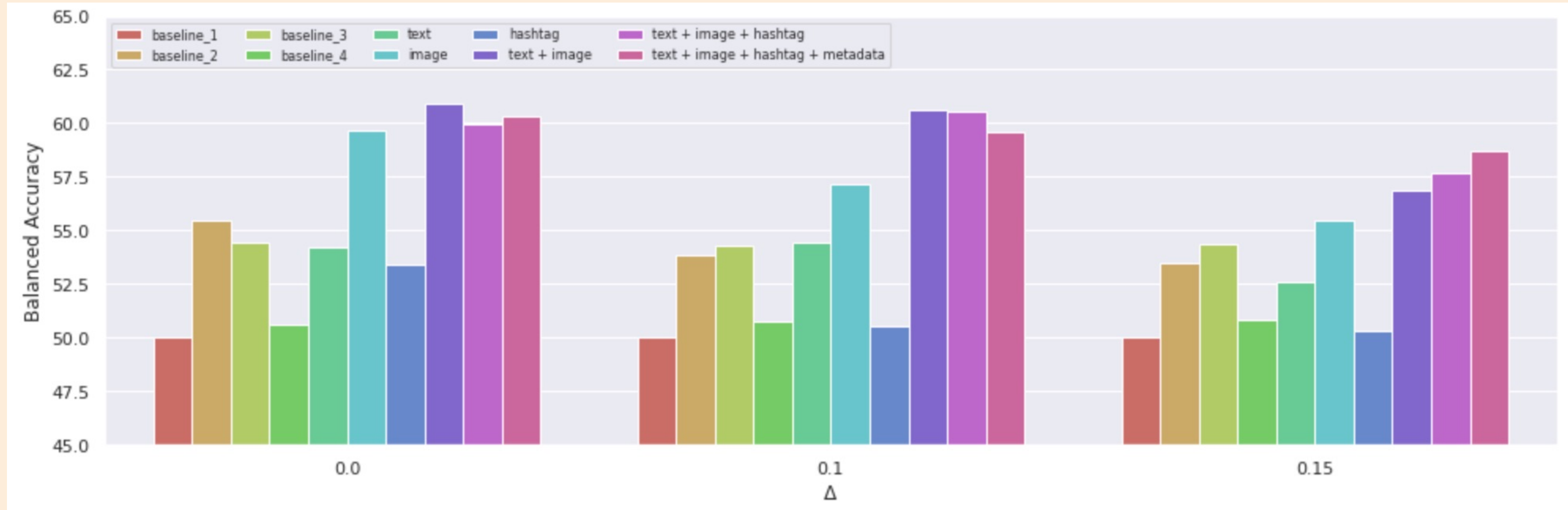

Figure 3. Model balanced accuracy

Hashtag Network

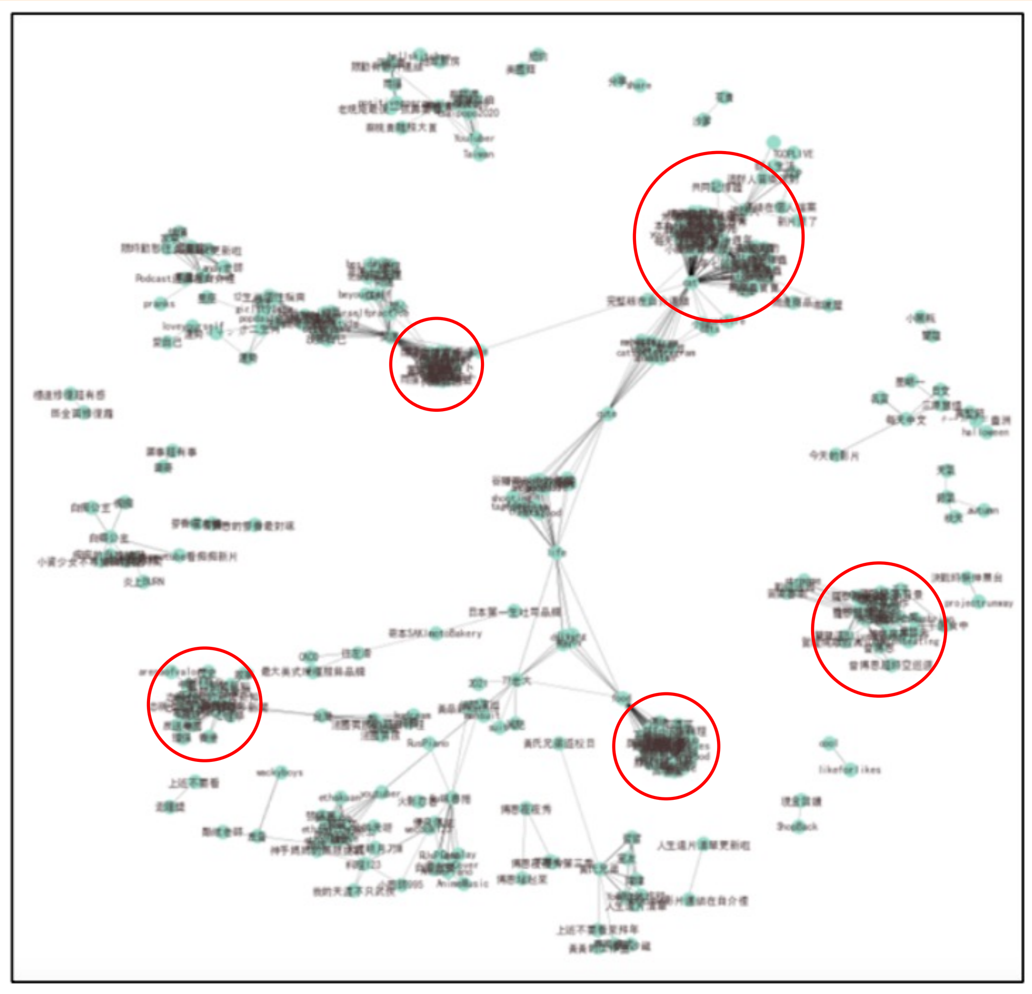

Figure 4. Simplified illustration of hashtag network

Topic 5 hashtag clusters	Top 5 topics
#貓 (cat)	解析_劇情_電影(movie)
#料理(cooking)	音樂_演唱會_歌曲(music)
#志祺七七 (Chih-Chyi77)*	衣服_西裝_穿搭(clothing)
#strnetwork*	料理_拌炒_醬油(cooking)
#占卜(fortune telling)	頭髮_髮型_短髮(hairstyle)

Figure 5. List of top hashtag clusters and topics

* Chih-Chyi77 and strnetwork are both Youtube creators in Taiwan

Conclusion

This paper proposes a multimodal framework incorporating hashtag network to predict popular Instagram posts of Taiwanese influencers. To be more precise, the hashtag modality of a post is constructed by fusing node embeddings from the hashtag network and topic embeddings from BERTopic. Instead of predicting raw likes or engagement, this study follows Carta et al. (2020) and builds a binary classifier that predicts posts as either popular or unpopular. Results indicate that the proposed multimodal framework surpasses all baselines and unimodal models. More importantly, the hashtag modality is shown to improve overall model performance at higher Δ levels, while its two components complement each other by capturing different post details.

Selected References

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